PIT: Optimization of Dynamic Sparse Deep Learning Models via Permutation Invariant Transformation

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Microsoft Research

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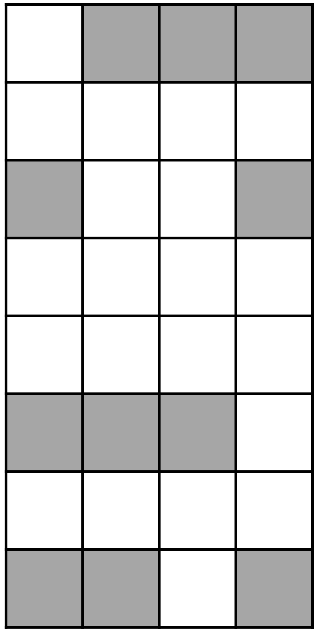
ADSLAB
先进数据系统实验室

Outline

- Background & Challenges
- Design & Implementation
- Evaluation

Background

- Sparse
  - Tensors with many zeros (token, weight, activation, etc.)



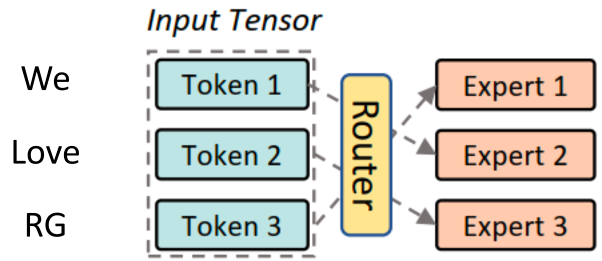
Tensor

Background

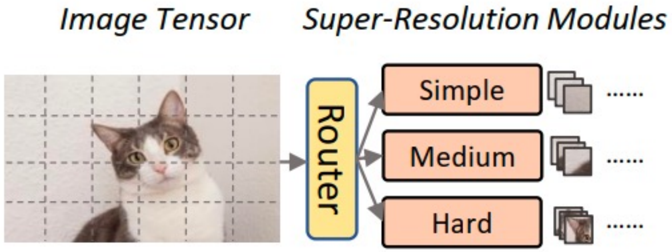
- Sparse
- Dynamic Sparse
  - Depend on inputs and is only known at runtime

Background

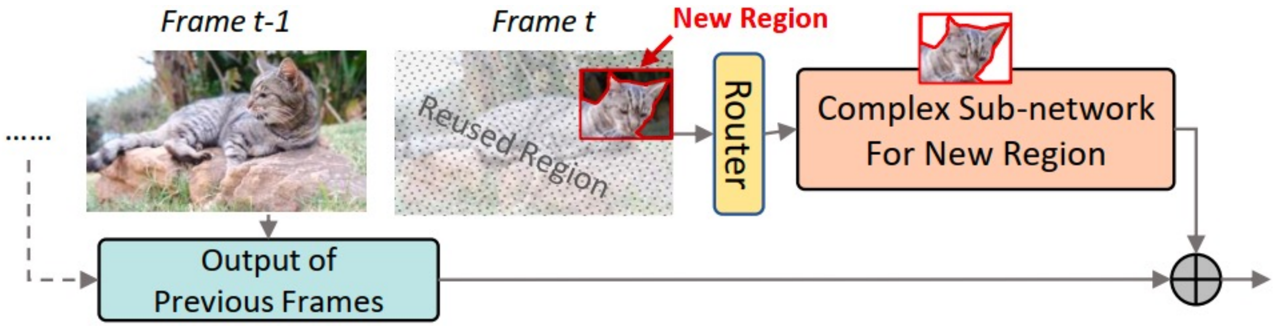
- Sparse
- Dynamic Sparse
  - ◆ Depend on inputs and is only known at runtime
  - ◆ **App-level**



(a) MoE



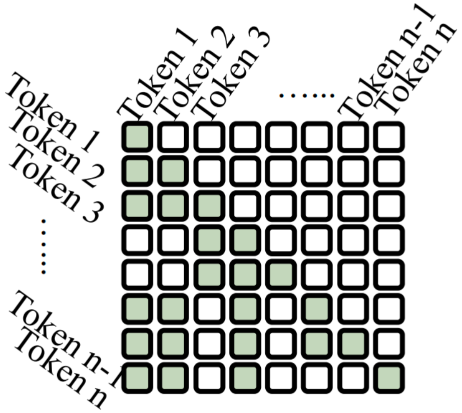
(b) Super-Resolution



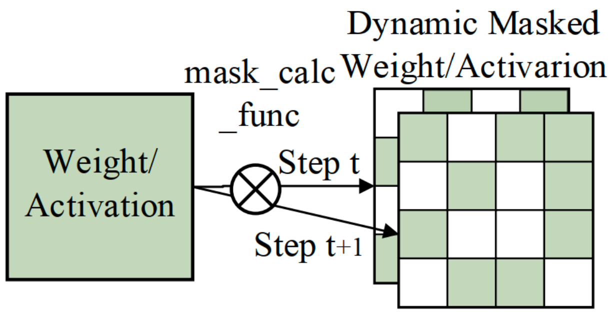
(c) Video Generation

Background

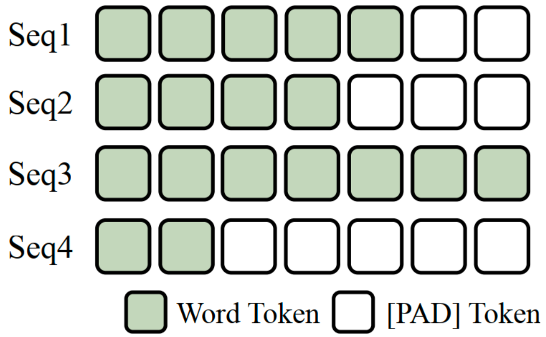
- Sparse
- Dynamic Sparse
  - ◆ Depend on inputs and is only known at runtime
  - ◆ App-level, **Tensor-level**



(a) Dynamic Attention[1,2]



(b) Sparse Training[3]

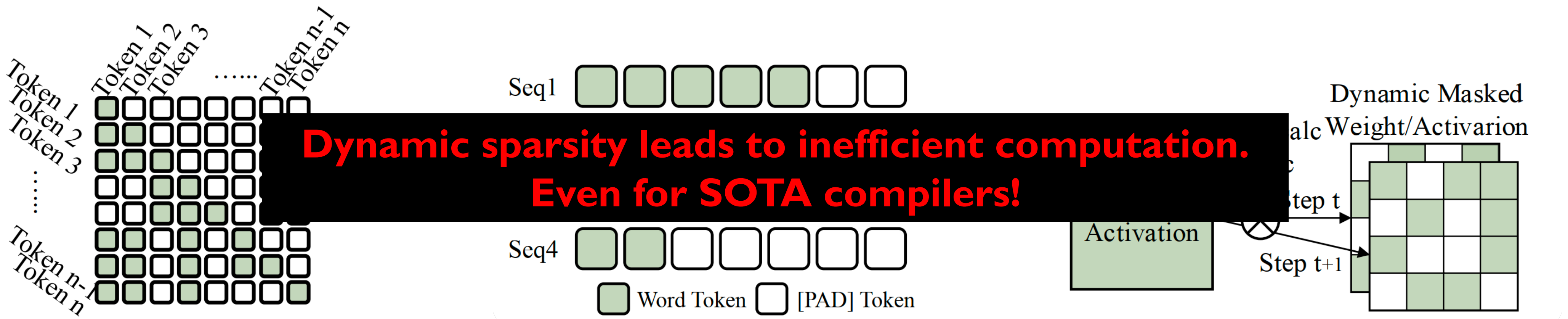


(c) Dynamic Sequence Length[4]

(1) *Generating long sequences with sparse transformers. arXiv preprint arXiv:1904.10509, 2019.*
(2) *Transformer acceleration with dynamic sparse attention. ArXiv preprint,abs/2110.11299, 2021.*
(3) *Block pruning for faster transformers. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing.*
(4) *Megablocks: Efficient sparse training with mixture-of-experts. MLSys2023, 2023.*

Background

- Sparse
- Dynamic Sparse
  - Depend on inputs and is only known at runtime
  - App-level, **Tensor-level**



Dynamic sparsity leads to inefficient computation.
Even for SOTA compilers!

(a) Dynamic Attention[1,2] (b) Dynamic Sequence Length[3] (c) Sparse Training[4]

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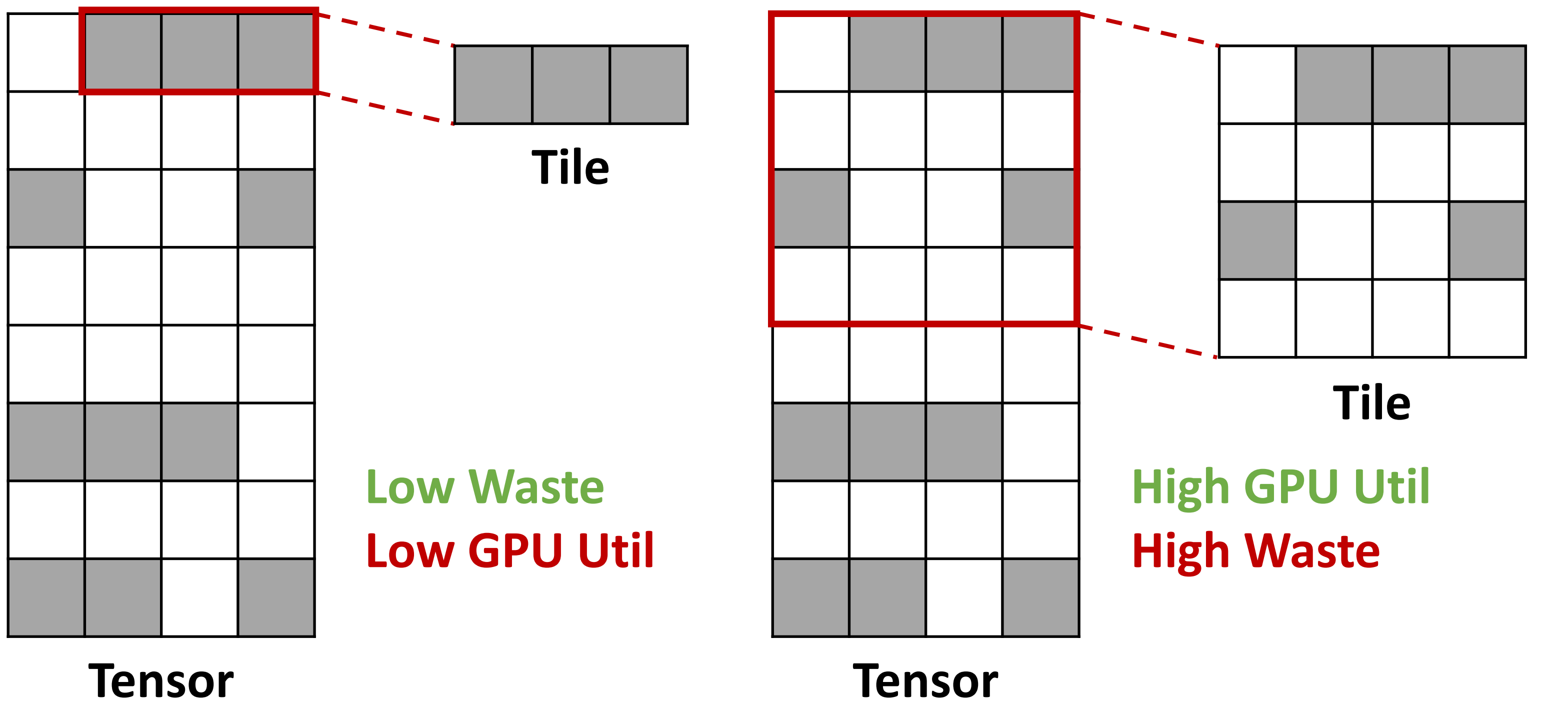
Background

- Tiling
  - Split tensor into smaller slices (tiles)
  - Reusing cached tiles can reduces the amount of data movement
  - Choosing an appropriate size can optimize data reuse

Background

- Tiling
- Tiling with Dynamic Sparsity
  - Trade-off exists between efficient tiling & sparsity shape alignment



Existing Solutions

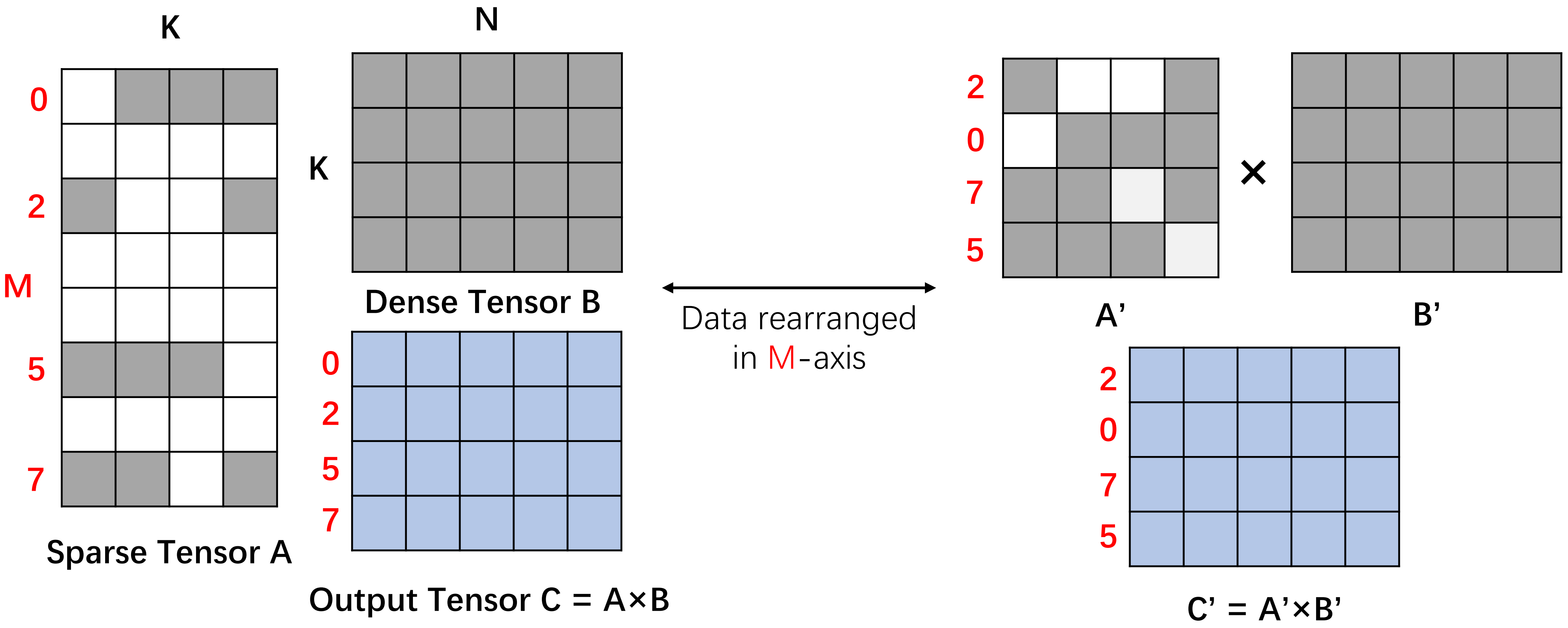
	Compiler/Library	Sparsity Aware	Dynamic Sparsity	Low Overhead
	Triton	☹	☹	☺
	ROLLER [OSDI’22]	☹	☹	☺
Specialized GPU Kernels	TVM-sparsity	☺	☹	☹
Specialized GPU Kernels	SparTA [OSDI’22]	☺	☹	☹
Convert to Special Format	cuSparse	☺	☺	☹
Convert to Special Format	Spunik [SC’20]	☺	☺	😐
	PIT [SOSP’23]	☺	☺	☺

Goal

- Try to find the most efficient tiling scheme
  - Minimize zero values
  - Maximize parallelism
  - Minimize latency

Opportunity

- Sparse data can be merge to efficient dense tile
  - With equivalent computation



Opportunity

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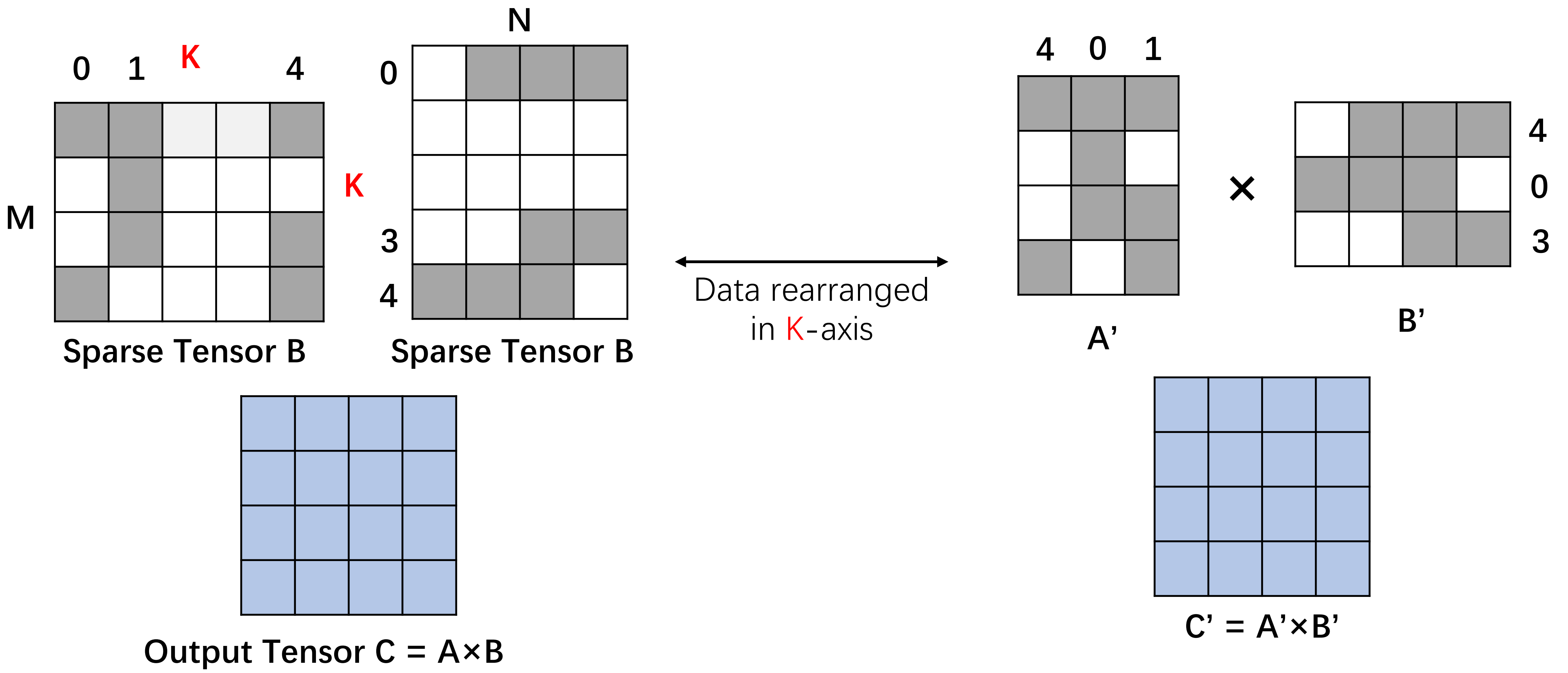
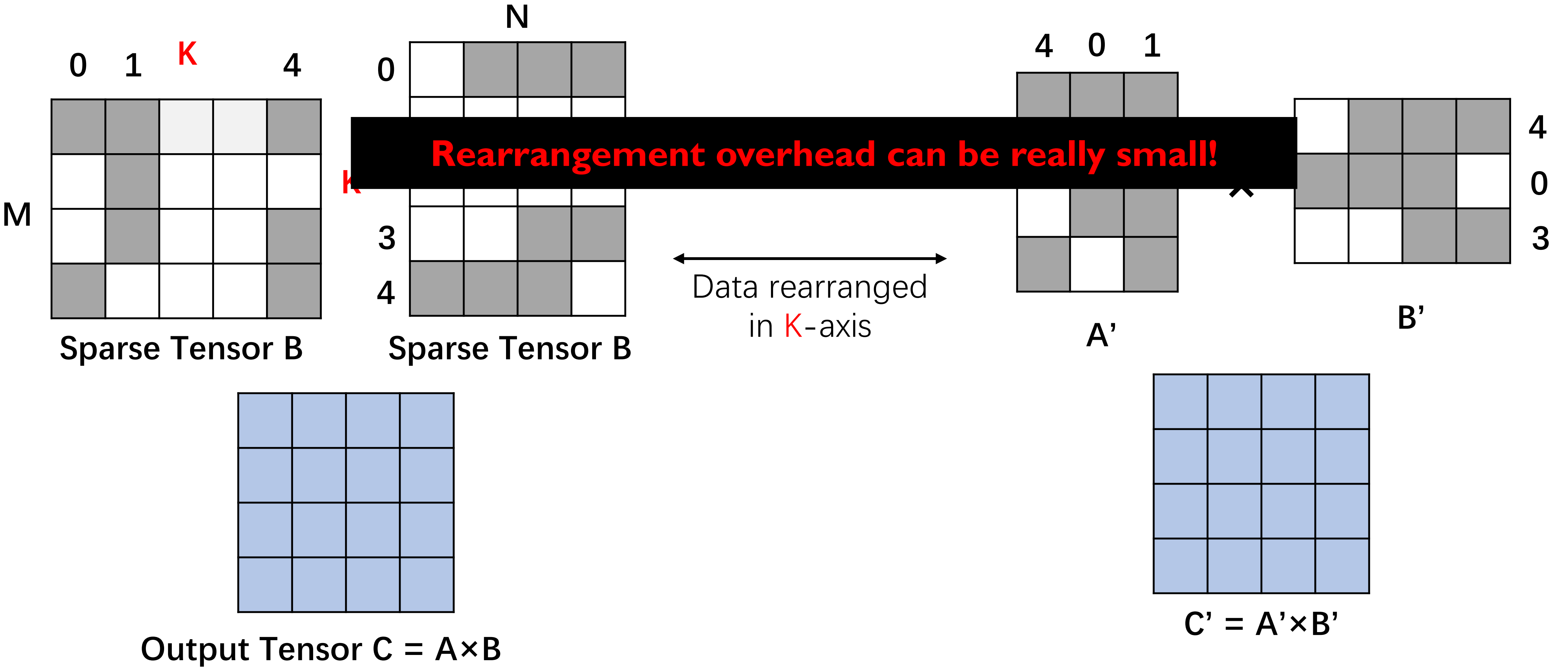
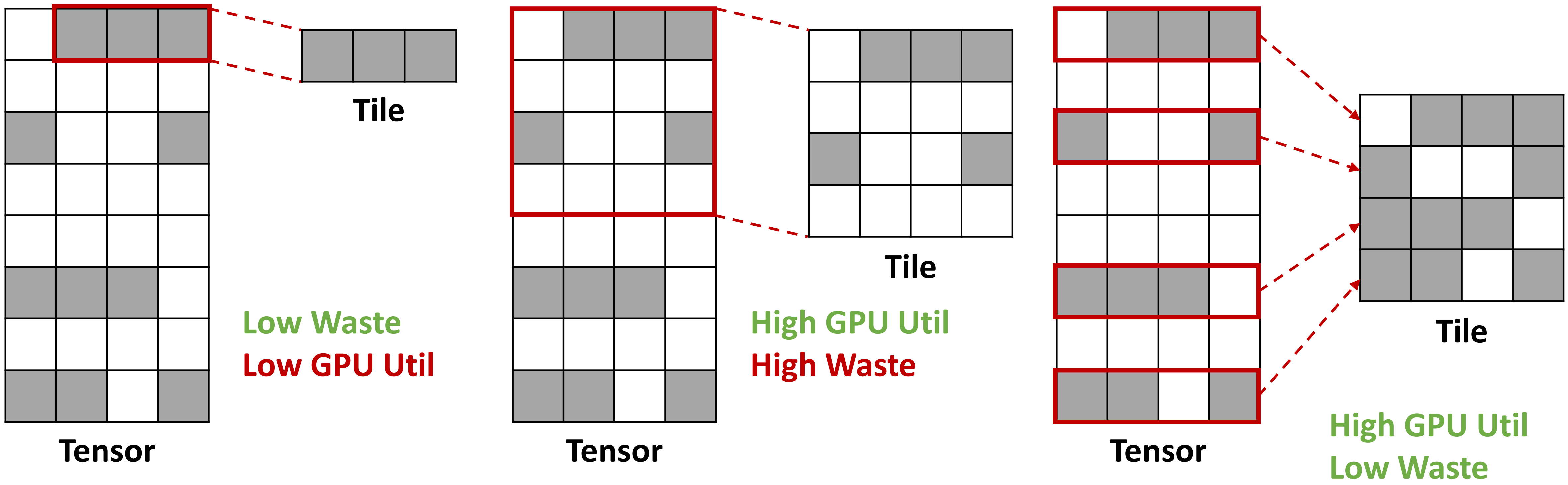


Opportunity

- Sparse data can be merge to efficient dense tile
  - ◆ With equivalent computation



Idea


Tile
Low Waste
Low GPU Util
Tensor
Tile
High GPU Util
High Waste
Tensor
Tile
Tensor
High GPU Util
Low Waste

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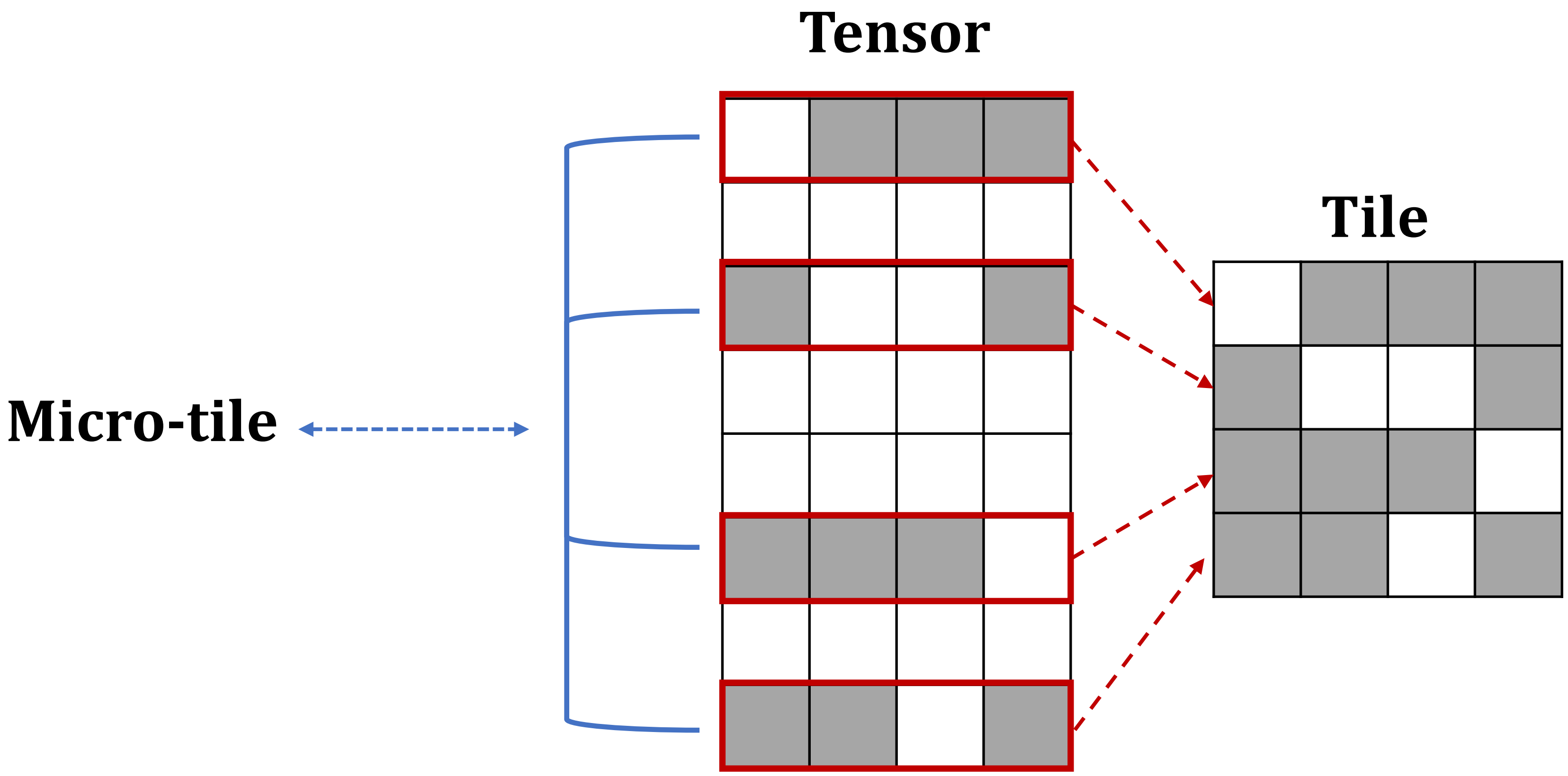
PIT Overview

- New Transformation Mechanism of PIT
- How to select Micro-tile and Kernel configuration
- Conversion Optimization for lower overhead

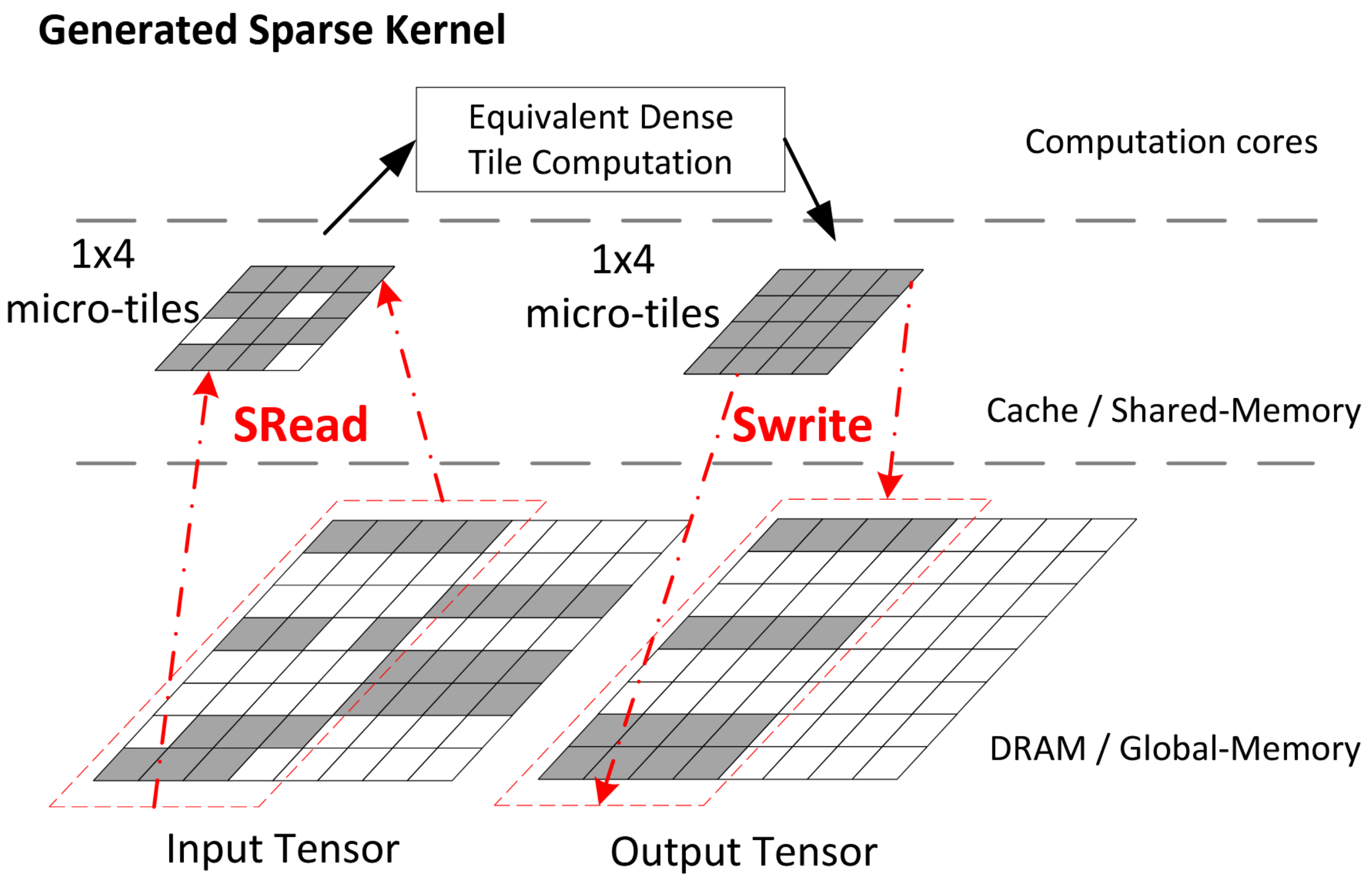
PIT Transformation Mechanism

- Micro-tile

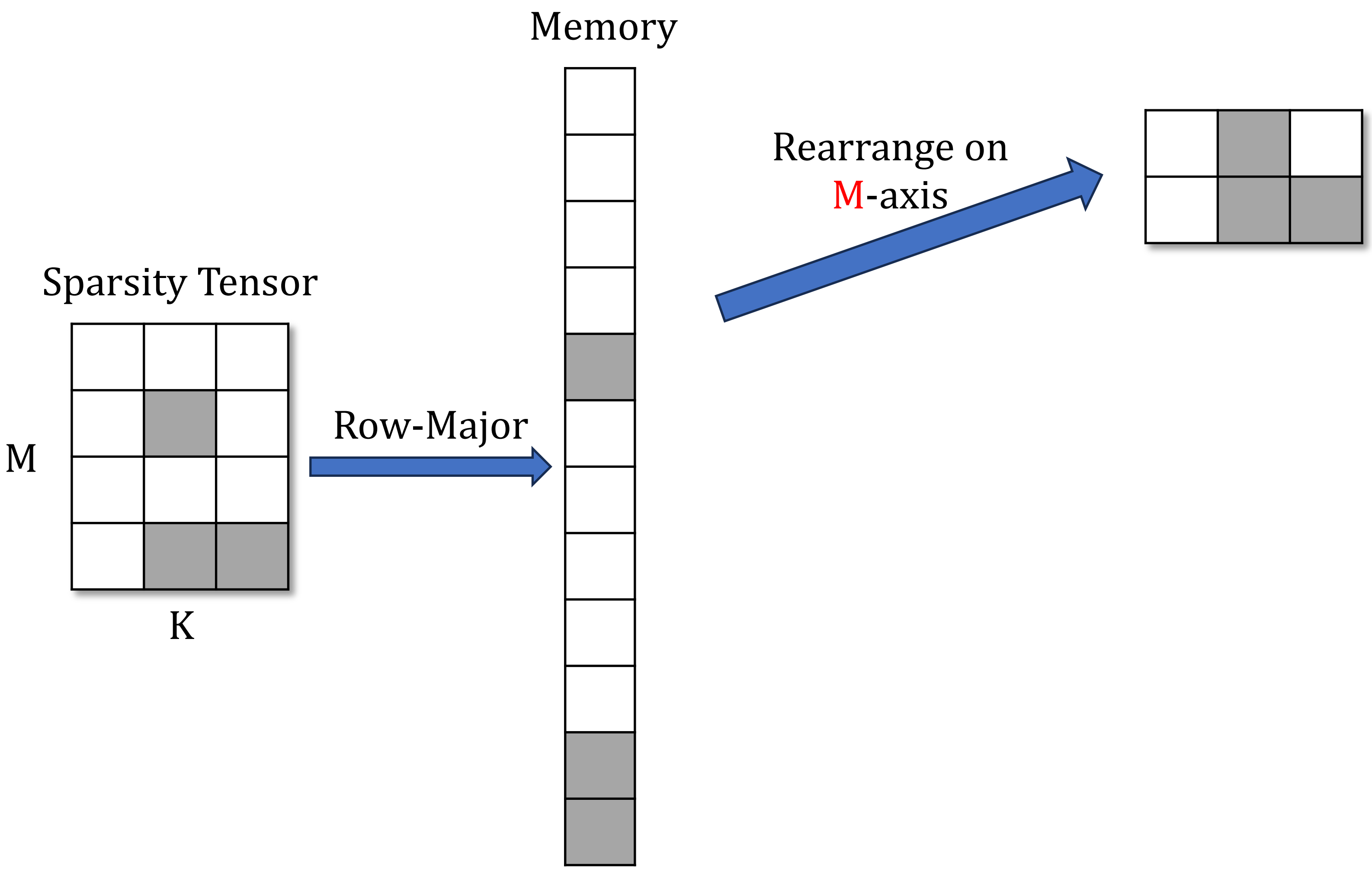


PIT Transformation Mechanism

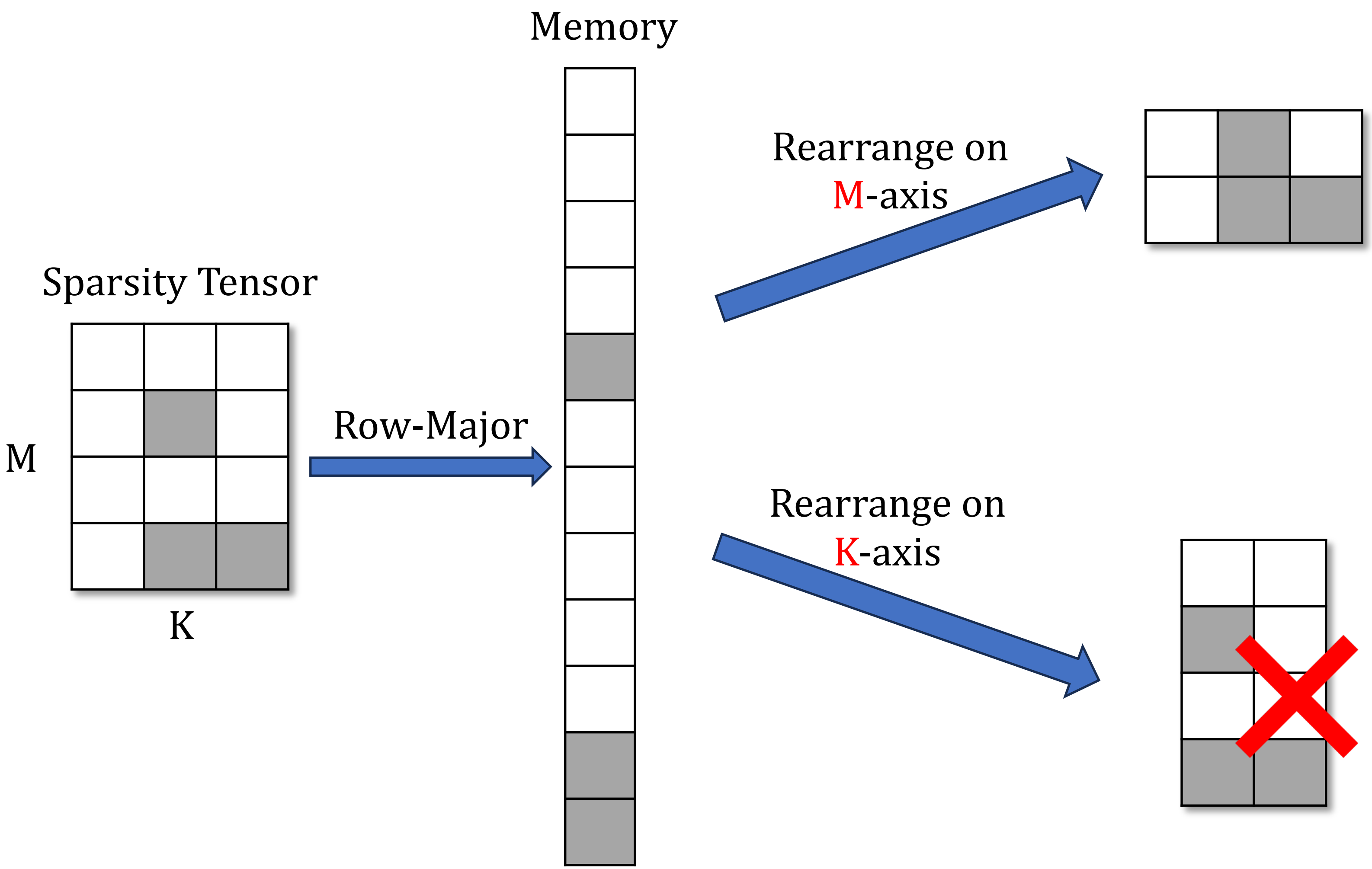
- New Primitives: SRead and SWrite



Micro-tile and Kernel Selection



Micro-tile and Kernel Selection



Micro-tile and Kernel Selection

Algorithm 1: Kernel selection for a dynamic sparsity operator.

Data: Op: A dynamically sparse operator,
D_{sparse}: A list of n sparsity samples of Op.
Result: $Best$: The best computation tile for Op.

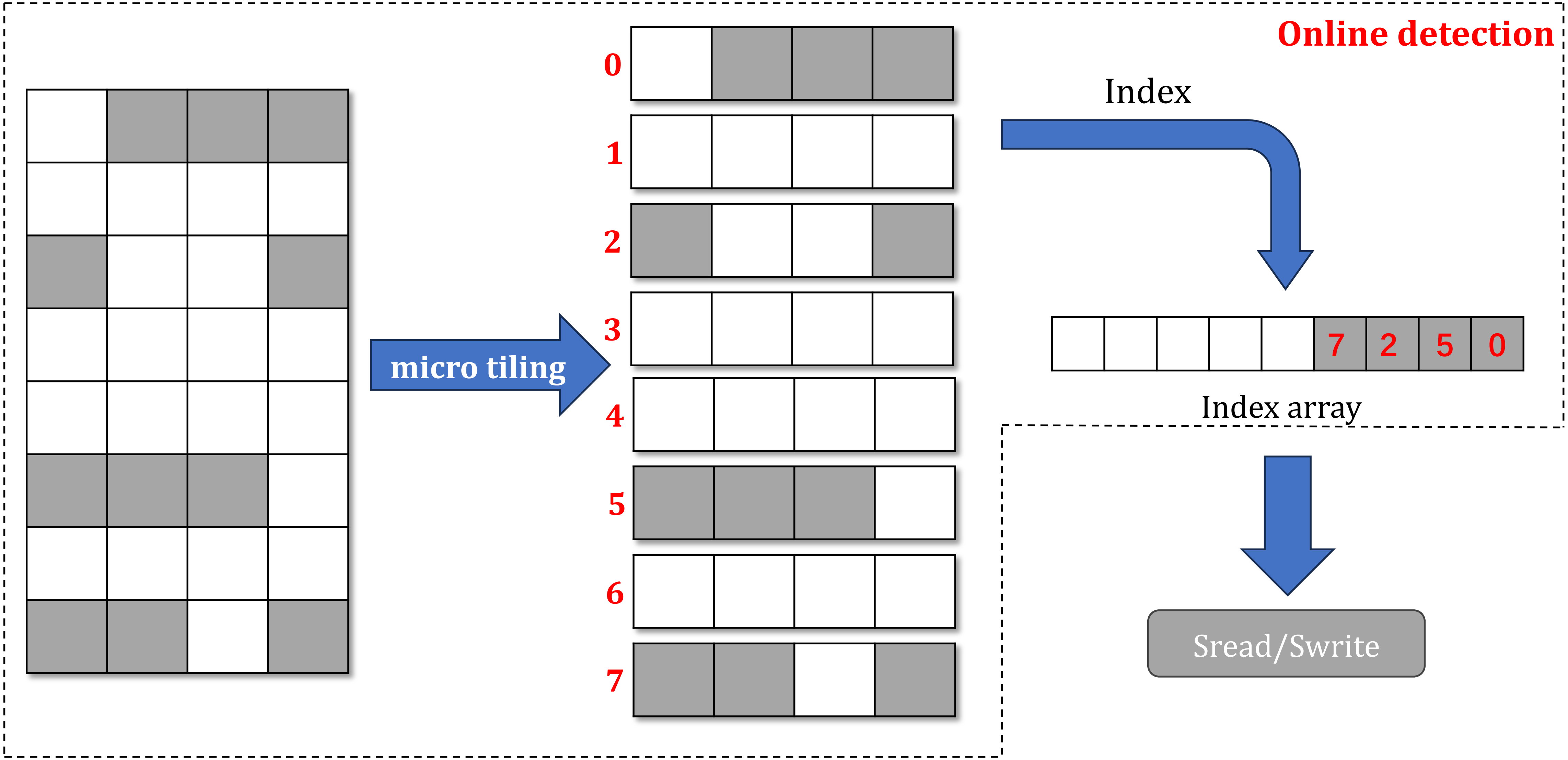
Function *KernelSelection*(D_{sparse}, Op):
  $Best$ = null; $Cost_{optimal}$ = inf;
  foreach $T \in$ *GetTilesFromTileDB*(Op) **do**
    foreach $A \in$ *GetPITAxis*(Op) **do**
      $Cost = 0$;
      $micro\_tile = GetMicroTile(T.SparseTensor, A)$;
      foreach $D \in D_{sparse}$ **do**
        Num_{tiles} = CoverAlgo(D, $micro\_tile$, A);
        $Cost \mathrel{+}= Num_{tiles} * T.tile\_cost$;
      if $Cost < Cost_{optimal}$ **then**
        $Best = S$;
        $Cost_{optimal} = Cost$;
  return $Best$;

Related to hardware instructions

Related to hardware instructions

Cost model

Online Sparsity Detection



Outline

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Evaluation

- Setup
- End-to-End Inference
  - Latency
  - Memory
- End-to-End Training
  - Latency
  - Memory
- Effectiveness of PIT Transformation
- Conversion Overhead
- Micro-Tile Online Searching

Evaluation: Concerns

- Questions to answer:
  - Q1: PIT’s advantages compared to baselines?
  - Q2: PIT’s performance in inference and training?
  - Q3: PIT’s conversion overhead?
  - Q4: Why certain baseline outperform other baselines?

Evaluation: Setup

- Baselines
  - PyTorch v1.11.0: Deep learning framework
  - DeepSpeed: Inference frameworks
    - Features: **Fuse** a layer into one operator in inference(but not in training)
  - TurboTransformers [SIGPLAN'21]:Inference frameworks
    - Features: optimized the **memory management** for varying input length
  - Tutel: Specific optimization techniques
    - Features: A efficient Mixture of Experts (MoE) implementation library

Evaluation: Setup

- Baselines
  - MegaBlocks [ML-Sys'23]: Inference frameworks
    - Features: Identify **blocky zero-element regions**, and skip them during calculations
  - SparTA [OSDI'22]: An optimization framework for **static** sparsity.
    - Features: Use efficient kernel calculations based on different sparse patterns
  - PyTorch-S: A variant of PyTorch that uses backends: cuSPARSE, Sputnik, Triton
    - cuSPARSE: mainly use Compressed Sparse Row (CSR) , provides efficient computational kernels
    - Sputni [SC'20]: Analyze the sparse pattern of the input matrix and select the most appropriate storage format and algorithm
    - Triton: A compiler and programming language, designed to simplify the process of writing GPU cores with high-performance

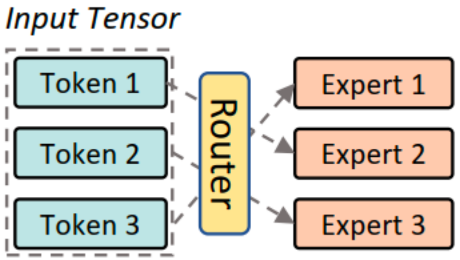
Evaluation: Setup

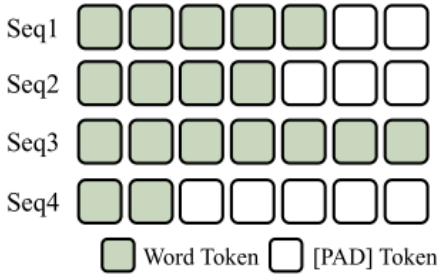
- Datasets and Hardware setup:

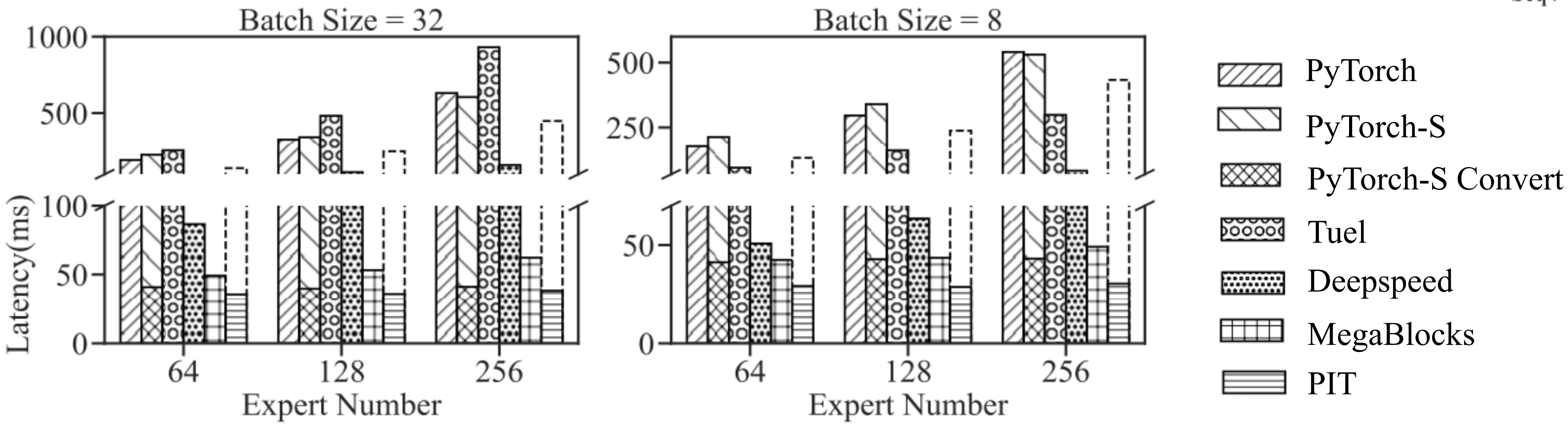
Models	Datasets	Model Structure	Precision	Devices
Switch Transformers[29]	MNLI [59]	Encoder Decoder MoE	fp16,fp32	A100
Swin-MoE [37]	ImageNet	Encoder MoE	fp16	A100
OPT [66]	Alpaca [58]	Decoder	fp32	V100
BERT [22]	GLUE [59], News [27] etc.	Encoder	fp32	V100
Longformer [14]	Arxiv [21]	Encoder	fp32	V100
MuseFormer [65]	LMD [54]	Decoder	fp32	V100

Evaluation: End-to-End Inference

- Switch Transformer (1x A100, FP16/FP32)
  - ◆ Latency: MegaBlocks stands out, but PIT is better
    - ▪ Without padding overheads
    - ▪ Simultaneous execution in MoE layers
    - ▪ Low data reorganization cost



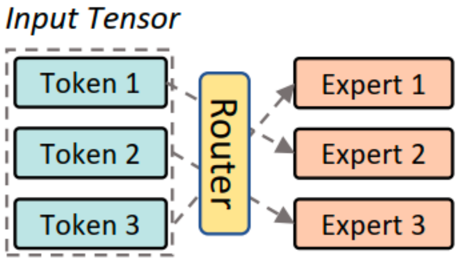


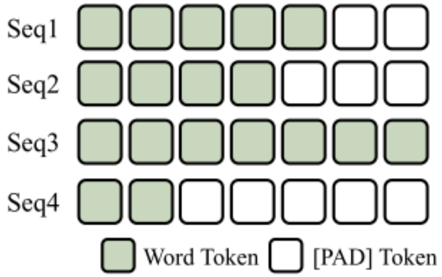


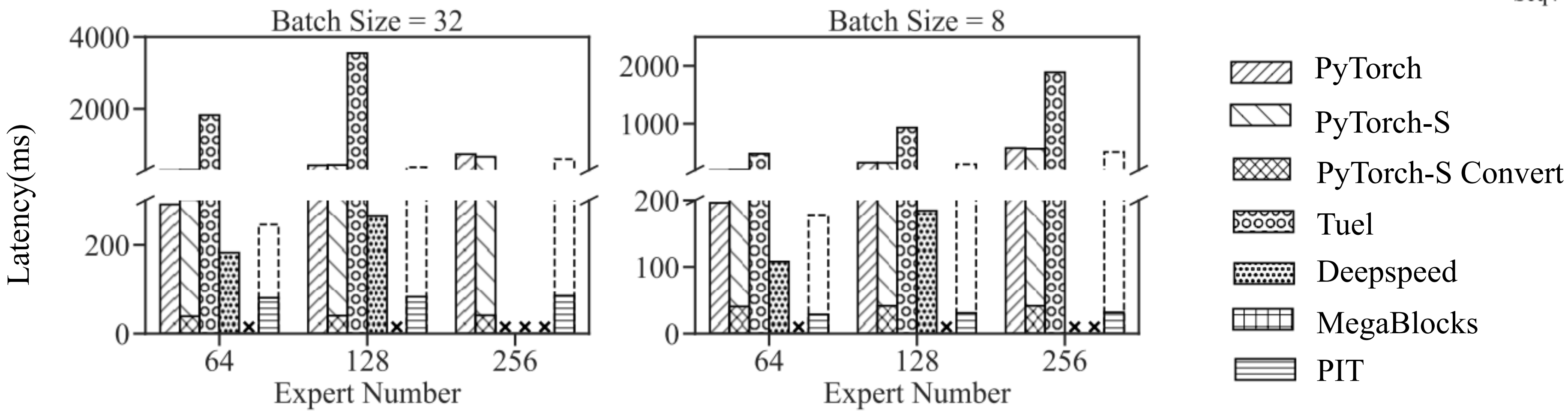
FP16 Latency

Evaluation: End-to-End Inference

- Switch Transformer (1x A100, FP16/FP32)
  - ◆ Latency: PIT is the lowest in FP32
    - Without padding overheads
    - Simultaneous execution in MoE layers
    - Low data reorganization cost



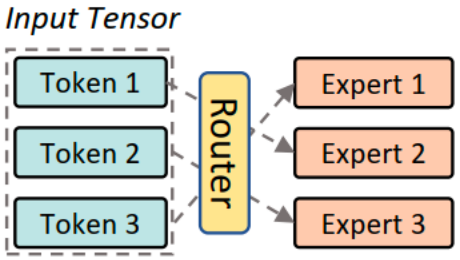


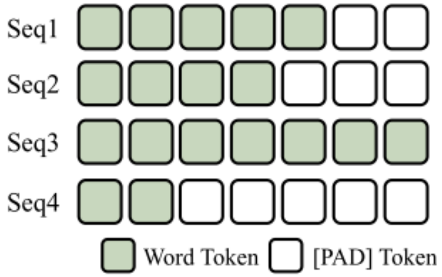


FP32 Latency

Evaluation: End-to-End Inference

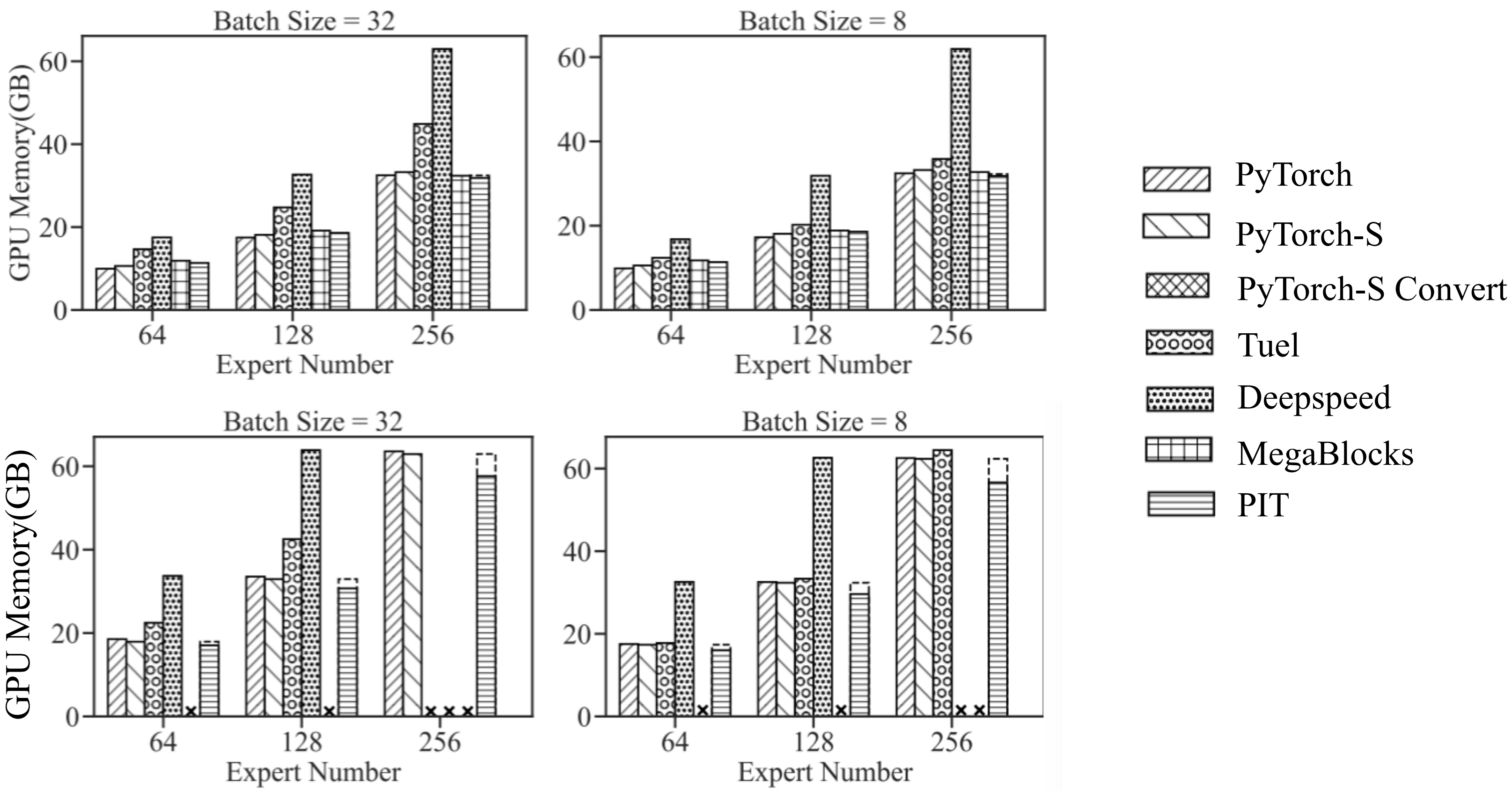
- Switch Transformer (1x A100, FP16/FP32)
  - Memory: PIT is the lowest in FP16 and FP32
    - Without padding





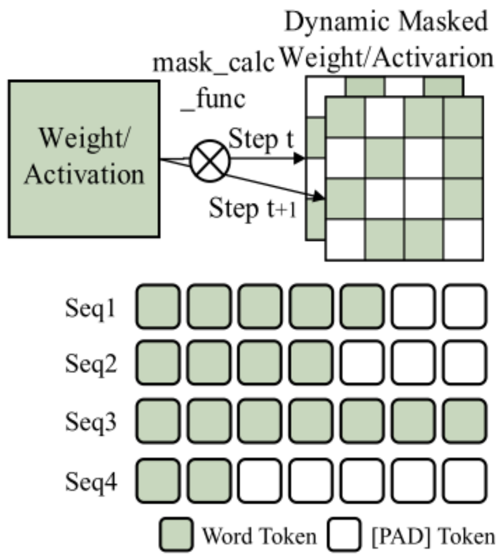
FP16

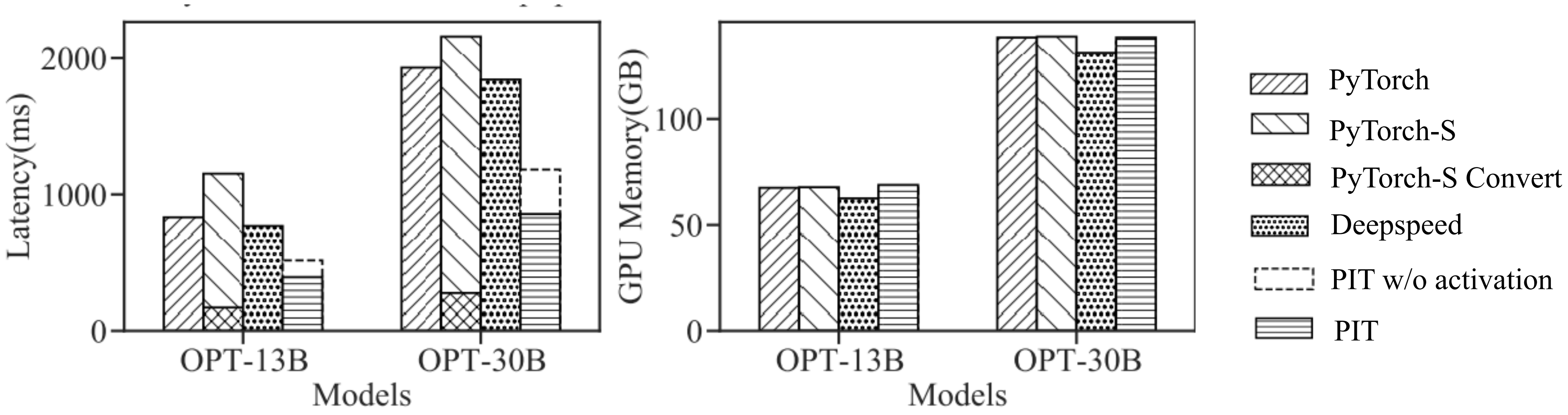
FP 32



Evaluation: End-to-End Inference

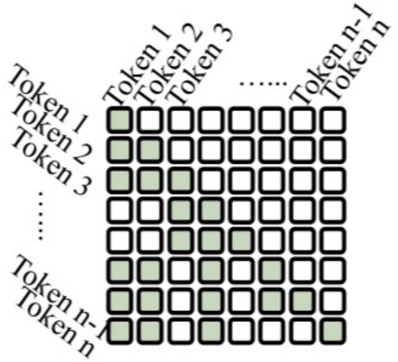
- OPT (8x V100, 13B/30B)
  - Latency: PIT is the lowest
    - Eliminating the padding overhead
    - Exploiting fine-grained sparsity in **ReLU** activation
  - Memory: DeepSpeed is the lowest
    - Deepspeed **fuse** a layer into one operator





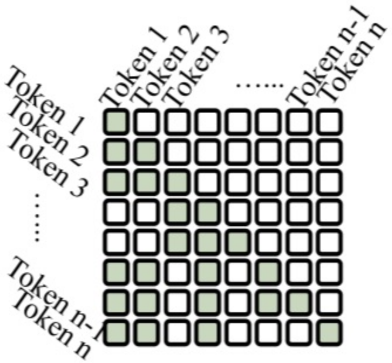
Evaluation: End-to-End Inference

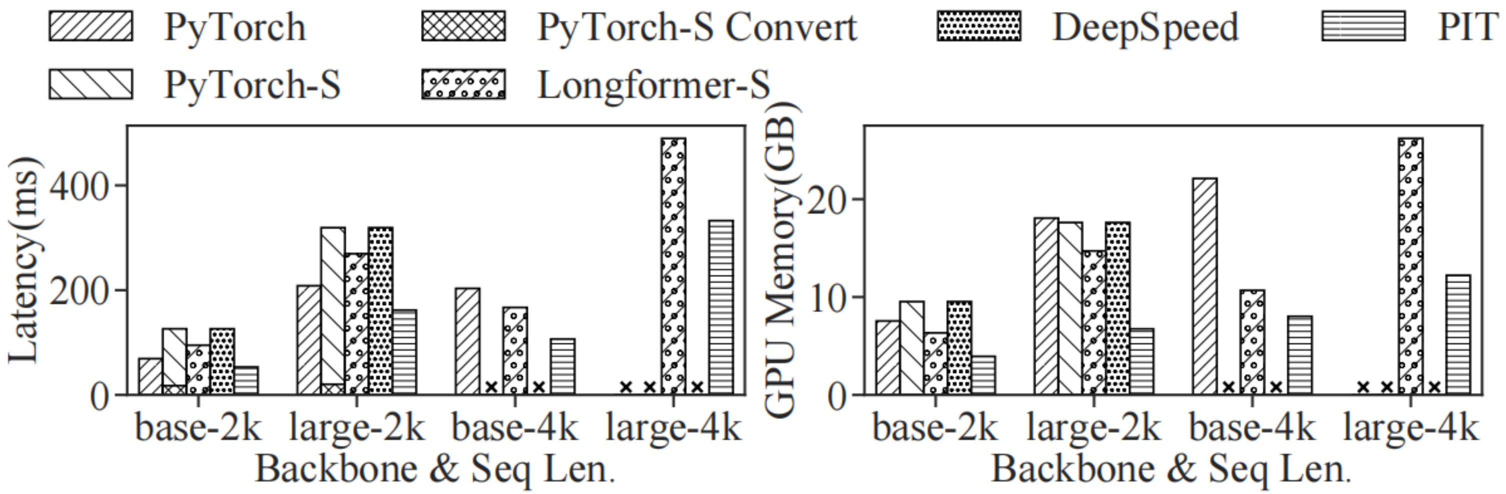
- Longformer(1x V100, FP32) Settings:
  - Sparsity: **Dynamic attention**
  - Input length: 2048/ 4096
  - Baselines:
    - Add **Longformer-S**
      - The sparse implementation specifically optimized for the Longformer
    - PyTorch-S and Deepspeed both selects **Triton** as the backend



Evaluation: End-to-End Inference

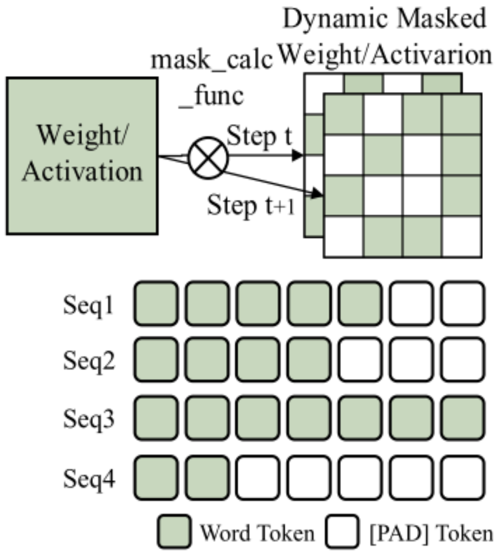
- Longformer(1x V100, FP32)
  - Latency: Longformer-S stands out, but PIT is better
    - Longformer-S: specifically optimized GPU kernels
    - PIT: no large data rearrangement overheads
  - Memory: PIT is the lowest
    - Without data re-arrangement (without **intermediate tensors**)

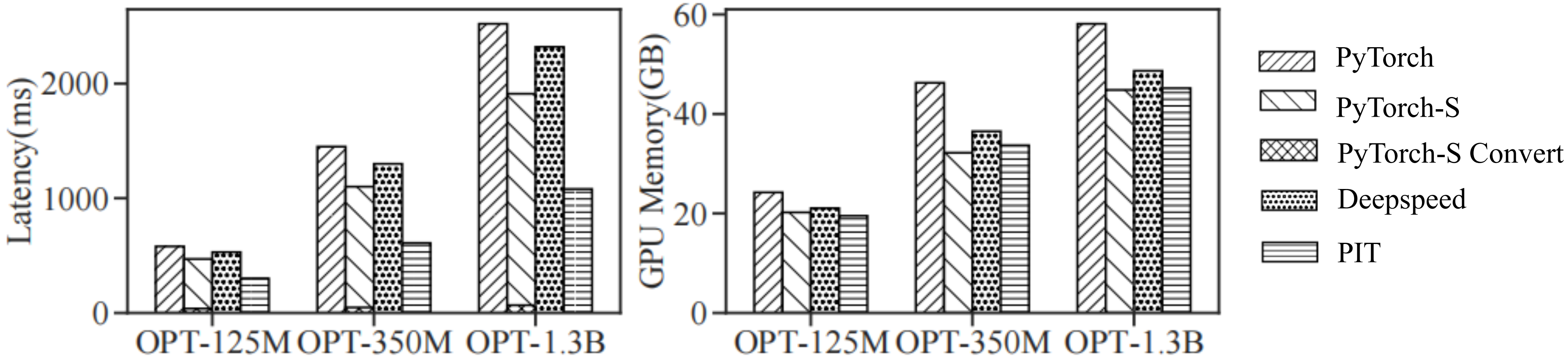




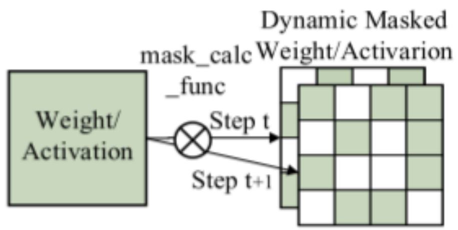
Evaluation: End-to-End Training

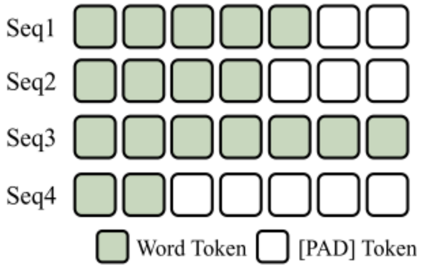
- OPT Training(1x A100, 125M/350M/1.3B)
  - Latency: PIT is the lowest
    - Without padding
    - Supports more fine-grained sparsity granularity
  - Memory: PIT is the lowest
    - Avoid reformatting data from dense to sparse formats





Evaluation: End-to-End Training

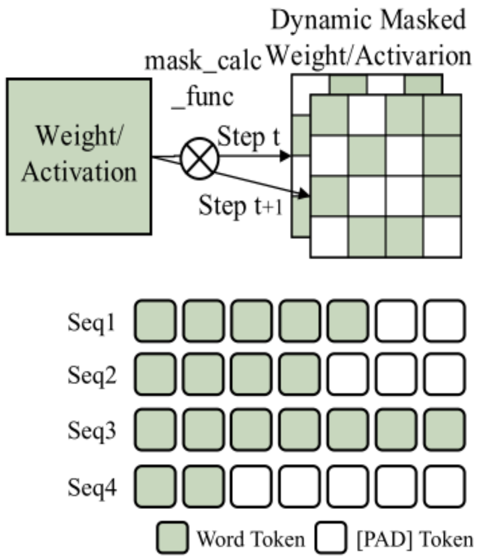


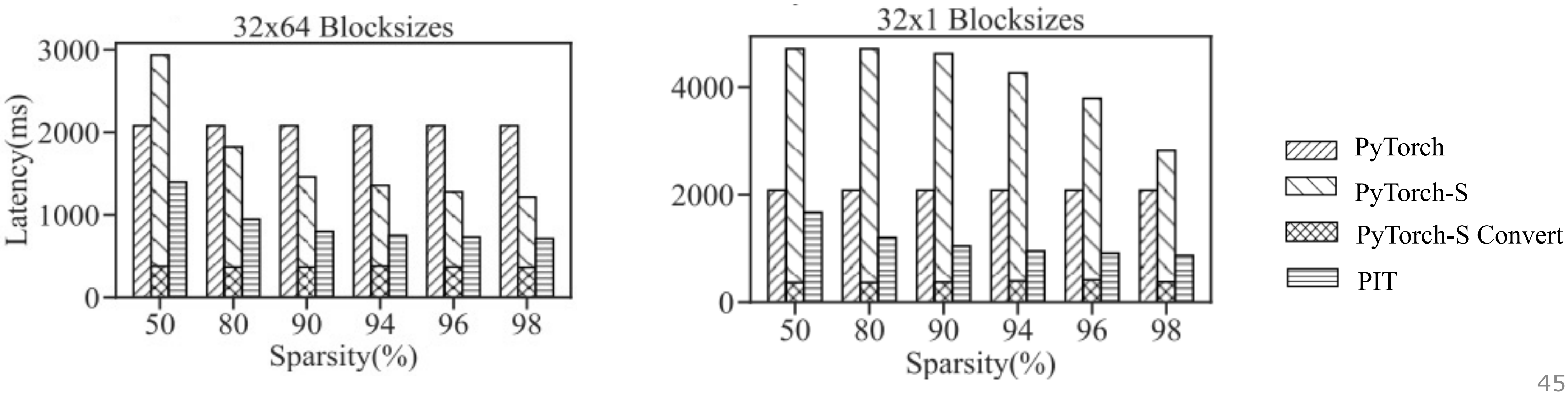


- BERT Training (1x V100) Settings:
  - **Iterative Pruning**
    - Generates a mask based on the weight's magnitude
  - Pruned using block-wise sparsity at **two granularities**: 32×64 and 32×1

Evaluation: End-to-End Training

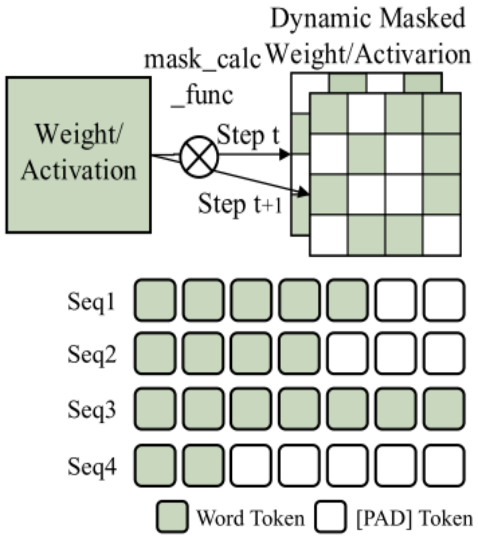
- Granularity: 32×64
  - Latency: PIT is the lowest
    - PyTorch-S suffer from heavy index construction
- Similar trend occurs on granularity of 32×1
  - Performance of PyTorch-S is worse than 32×64
  - But accuracy increases slightly

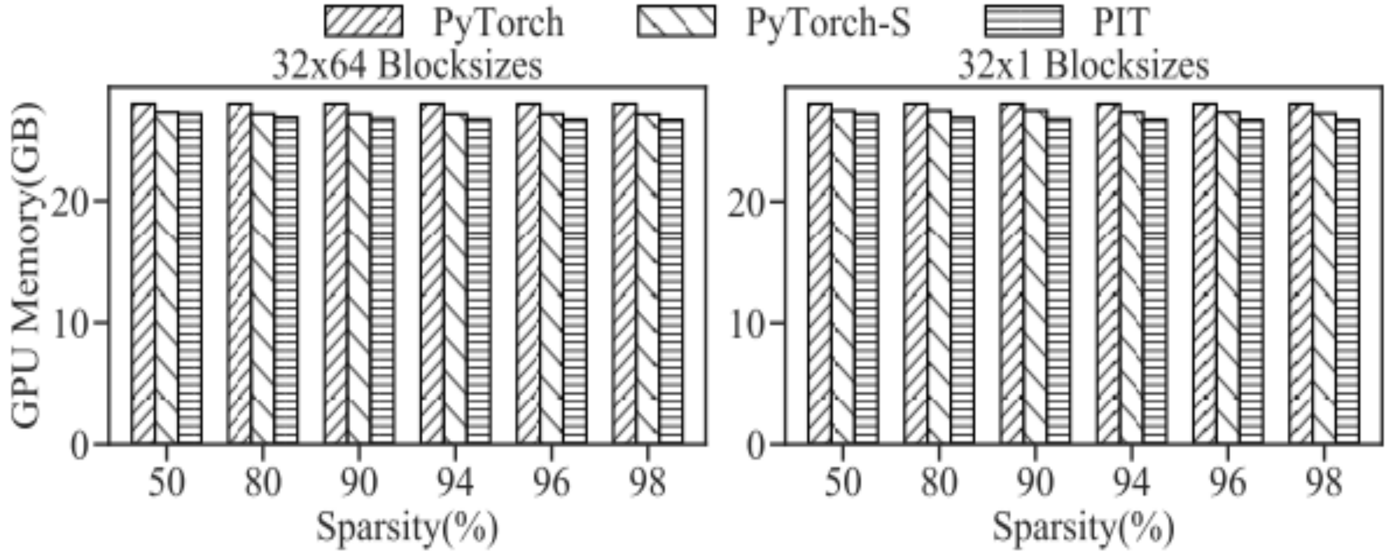




Evaluation: End-to-End Training

- BERT Training (1x V100):
  - Memory: PIT is similar to baselines in both granularity, footprint dropped slightly as sparsity ratio increased
    - Weight tensors take up only a small fraction of memory



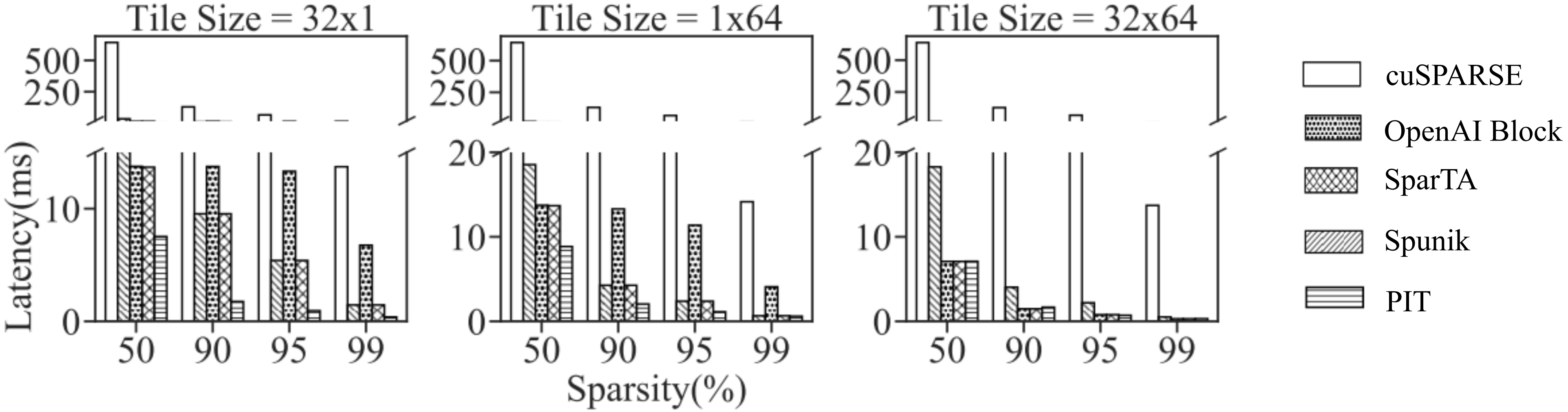


Evaluation: Effectiveness of PIT Transformation

- Exp1: PIT Transformation on Dense Kernels:
  - Experiments Settings:
    - Sparse matrix with different sparsity granularities and shapes
    - Baselines: Sparse libraries, including cuSPARSE, Sputnik, OpenAI Block Sparse (Triton), and **SparTA** (state-of-art **static** sparsity optimization)
    - Use a **static** sparsity pattern to evaluate the computation efficiency

Evaluation: Effectiveness of PIT Transformation

- Exp1: PIT Transformation on Dense Kernels:
  - PIT, SparTA, and OpenAI Block Sparse have **similar latency in 32×64**
    - They use the same dense computation tile
  - cuSPARSE and Sputnik perform poorly
    - High conversion overheads
    - Poor kernels implementations
  - PIT perform **best** in **32×1 and 1×64**
    - support changing smaller micro tiles under small sparsity granularity

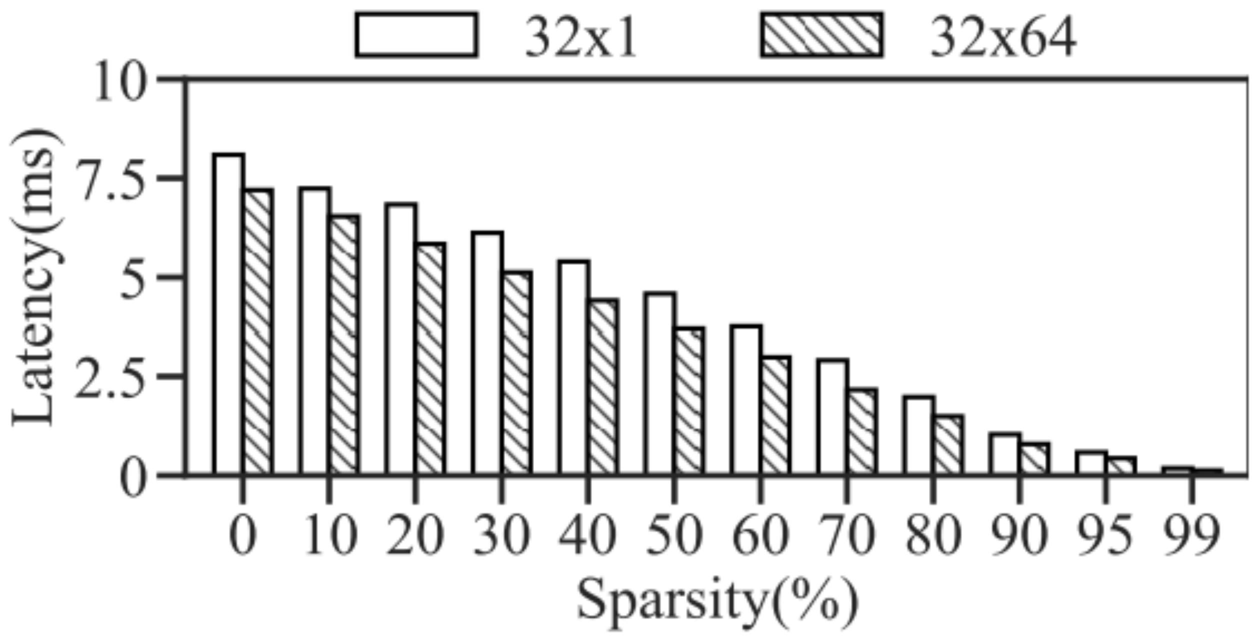


Evaluation: Effectiveness of PIT Transformation

- Exp2: PIT transformation on hardware instructions:
  - Purpose: Show PIT transformation can adapt to the constraints of hardware instructions
  - Experiments Settings:
    - Two different sparsity granularities: 32×1 and 32×64
    - [4096, 4096]×[4096, 4096] matrix multiplication
    - Hardware instructions: **Wmma**, only supports three shapes ([16, 16]×[16, 16],[32, 8]×[8, 16], [8, 32]×[32, 16]) in half-precision

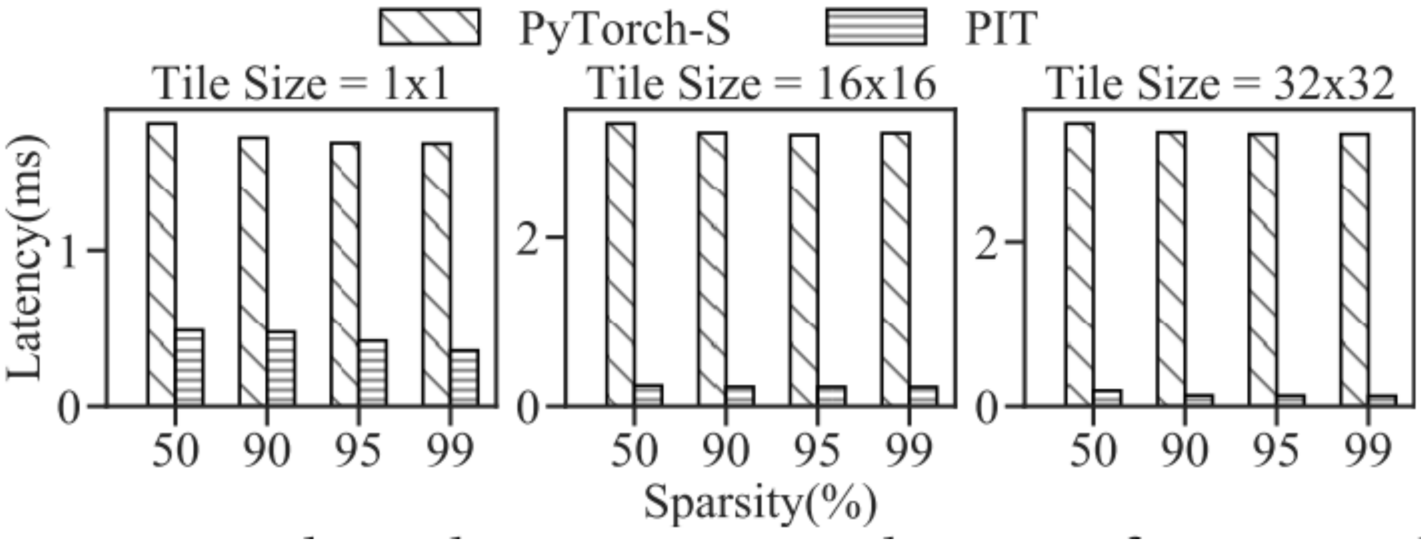
Evaluation: Effectiveness of PIT Transformation

- Exp2: PIT transformation on hardware instructions:
  - The two sparse kernels generated by PIT has **similar latency** at different sparsity ratios
  - PIT transformation introduces little overhead



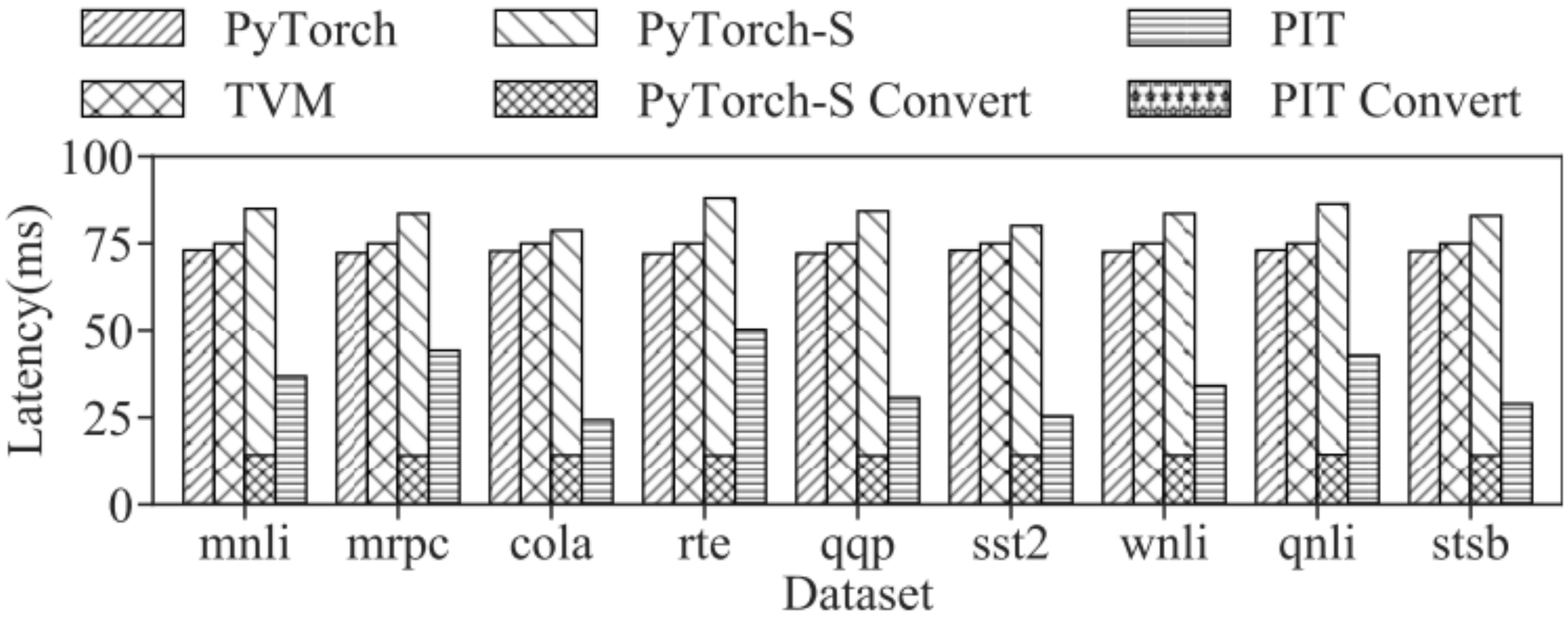
Evaluation: Conversion Overhead

- Exp1: Comparion of conversion latency(1x V100):
  - Settings:
    - Different sparsity granularities and sparsity ratios
  - Convert Latency:
    - PIT is 3.6x~4.7x faster than cuSPARSE at 1× 1 granularity
    - 11.2x~14.2x faster than Triton at 16× 16 granularity
    - 13.3x~26.5x faster than Triton at 32× 32 granularity



Evaluation: Conversion Overhead

- Exp2: The proportion of the conversion overhead:
  - Conversion accounts for 0.7% to 1.1% of the end-to-end latency



Evaluation: Micro-Tile Online Searching

- Different sparsity patterns and different sparsity ratios may lead to different optimal micro-tiles
  - PIT balance between the efficiency and the waste
  - Cost 30us~100us for PIT to search (fast enough)

Sparsity Granularity	Origin Sparsity Ratio(%)	Micro Tile	Sparsity Ratio After Cover (%)	Origin Dense Kernel	Latency (ms)
(2,1)	95	(16, 1)	66.39	$[16, 32] \times [32, 128]$	8.04
(2,1)	99	(8, 1)	96.06	$[8, 32] \times [32, 128]$	2.34
(4,1)	95	(16, 1)	81.45	$[16, 32] \times [32, 128]$	4.29
(4,1)	99	(16, 1)	96.05	$[16, 32] \times [32, 128]$	1.37
(8,1)	95	(8, 1)	95	$[8, 32] \times [32, 128]$	2.34
(8,1)	99	(32, 1)	96.02	$[32, 64] \times [64, 32]$	0.90
(32, 1)	95	(32, 1)	95	$[32, 64] \times [64, 32]$	0.94
(32, 1)	99	(32, 1)	99	$[32, 64] \times [64, 32]$	0.39

Summary

- Pros:
  - ◆ PIT achieves increased efficiency in dynamic sparsity.
  - ◆ PIT supports various models, including those with static sparsity.
  - ◆ PIT minimizes additional overhead by online sparsity detection.

- Further thoughts:
  - ◆ Trade-off between rearrange granularity & efficiency
  - ◆ Support for different operators
  - ◆ Support for App-level sparsity
  - ◆ Profiling is still heavy